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Design and Implementation of Biologically Realistic Signal to Symbol Translators

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ABSTRACT

This paper reviews the problem of translating signals into symbols preserving maximally the information contained in the signal time structure. In this context, we motivate the use of nonconvergent dynamics for the signal to symbol translator. We then describe a biologically realistic model of the olfactory system proposed by Walter Freeman that has locally stable dynamics but is globally chaotic. We present results of simulations and measurements obtained from a fabricated analog VLSI chip.

1. INTRODUCTION

1. Introduction

There are many important differences between biological and man-made information processing systems. Animals have goal driven behavior and have explored inductive principles throughout the course of evolution to work reliably in a nonGaussian, nonstationary, nonlinear world. Autonomous man-made systems with sensors and computational algorithms (animats) are still unable to match these capabilities. The processing device that transforms signals into symbols is called here the signal-to-symbols translator (SΣT). We can specify an optimal SΣT as a device that is able to capture the goal-relevant information contained in the signal time structure and map it with as little excess irrelevant information as possible to a stable representation in the animat's computational framework.

A framework where the SΣTs is modeled as a dynamical system coupled to the external world seems a productive alternative. We will center the discussion in distributed, adaptive arrangements of nonlinear processing elements (PEs) called coupled lattices [3]. In neurocomputing content addressable memories (CAMs), both static or dynamic (Hopfield networks) with fixed points have been proposed and shown useful. However, we are slowly realizing that the limited repertoire of dynamical behavior (fixed points) implemented by the DCAMs constrain their use as information processing devices for signals that carry information in their time structure. For instance, the point attractor has no dynamical memory (i.e. the system forgets all previous inputs when it reaches the fixed point); while the dynamic memory of the limit cycle is constrained to the period; only chaotic systems display long term dynamic memory due to the sensitivity to initial conditions. This sensitivity carries the problem of susceptibility to noise, but a possible solution is to utilize a chaotic attractor created by a dynamical system with singularities of at least second order (third order ODE). A chaotic attractor is still a stable representation, might exist in a high dimensional space (much higher than the dimensionality of our 3D world), and more importantly its dimensionality can be controlled by parameters of the SΣTs. Forseeably such systems are capable of using the inner structure of trajectories within the attractor for very high information storage and rapid recall, but we still do not fully understand how to control the stability of recall in particular in the presence of noise.

Our aim is to construct a SΣT that operates in accordance with the neurodynamics of the cerebral cortex, and that has the sensitivity, selectivity, adaptiveness, speed, and tolerance of noise that characterizes human sensation. We will be using a model of the rabbit olfactory cortex proposed by Walter Freeman to develop and implement an analog VLSI version of a biologically realistic SΣT [1]. The core of the model is the KII network.

2. MESOSCOPIC DYNAMICS: A QUICK OVERVIEW

We will be modeling brain dynamics at the level of million of cells, which is called the mesoscopic level [2]. The advantage of the mesoscopic level is that it is able to describe interactions among sufficient large populations of cells that are relevant to probe information processing. Action potentials limit the modeling to relatively small number of cells, while the electroencephalogram describes too global interactions.

Our unit of processing will be called a processing element (PE). PEs are modular and formal representations of populations of neurons in the mammalian brain. The representation of responses is done by means of density functions that measure the pulse to wave conversion, e.g. from a firing pulse density of a set of neurons to the current density and back to a pulse density. Hence, the functions are continuous in time, magnitude and space. From biological evidence Freeman as proposed the following K0 structure [1] shown in figure 1 to represent a population of neurons.

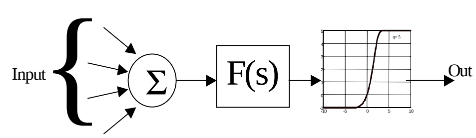

Figure 1.- K0 model diagram (excitatory).

The K0 PE comprises a summing input node where the spacial inputs converge into a 2^{nd} order dynamics block F(s) represented

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Abstract

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by (1). The output signal is the result of a pulse to wave density conversion function. This signal is then reconverted into a pulse density signal by means of a non-symmetric non-linear function represented also in figure 1. This is the wave to pulse conversion phase and, in terms of densities, is functionally represented by (2). Figure 2 shows the non-linearity for different 'q' values.

$$\frac{1}{a \cdot b}\left(\frac{\partial^2}{\partial t^2}x(t) + (a+b)\frac{\partial}{\partial t}x(t) + a \cdot bx(t)\right) = f(t) \quad (1)$$

$$Q(x(t), q) = \begin{cases} q(1 - e^{-(e^{x(t)}-1)/q}) & \text{, If } \; x(t) > x_0 \\ -1 & \text{, If } \; x(t) < x_0 \end{cases} \quad (2)$$

$$x_0 = \ln(1 - q\ln(1 + 1/q))$$

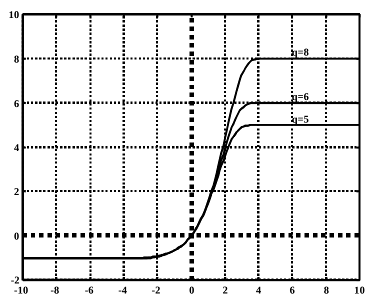

Figure 2.- Non-symmetric non-linearity function (eq. (2)).

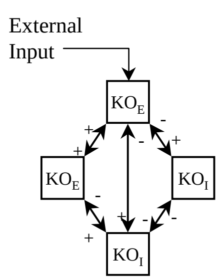

Figure 3.- KII PE representation (each square represents a K0 of figure 1).

The K0 is the building block of an hierarchical family that models different types of anatomical connections. For instance, in the olfactory system of the rabbit, the K0 network models the periglomular layer (only excitatory cells). The KII is a special arrangement of K0s forming a multi-input multi-output (MIMO) network. The arrangement mimics biological evidence and is shown in figure 3. The (+) and (-) signs describe excitatory and inhibitory connections. The inhibitory K0 is simply obtained by negating the output of figure 1 (flipping the sigmoidal non-linearity over the x axis). Under correct parameter sets, defined as interconnection gains, the KII PE behaves as an oscillator controlled by the input. It is zero for zero input and oscillates if the input (an external signal shown in figure 3) amplitude rises.The KII network is a lattice of KII PEs that models the olfactory cortex. The excitatory connections among KII PEs are modulated by Hebbian learning, while the negative connections among KII PEs are fixed. Functionally speaking, the KII network is an associative memory, creating a mapping from input patterns to a distinctive spatio temporal pattern of activity for each input over the coupled lattice.

The olfactory cortex is a hierarchical arrangement of KII networks, tightly coupled by dispersive delays. In our KIII, we model the olfactory bulb (OB), the anterior olfactory nucleus (AON), the prepiriform cortex (PC), and the entorhinal cortex (EC). Since the individual KII oscillators in each of these cortical areas have different intrinsic oscillating frequencies and are tightly coupled by delays connections, the KIII network displays nonconvergent (chaotic) dynamics. Hence, it is locally stable but globally unstable. With no input, the KIII model lies in a high dimensional chaotic state. Once it is activated, the system dynamics quickly collapse to a lower dimensional attractor (an "attractor wing") where the input is recognized. When the input is taken out, the system state returns to the high dimensional chaotic regime, waiting for a new input. The information processing characteristics of this design have not been thoroughly investigated yet.

3. ANALOG VLSI CIRCUIT IMPLEMENTATION

The formulation of the cell assembly's behavior in terms of nonlinear dynamics opens the door to analog VLSI simulations. This is one of the advantages of the nonlinear dynamics framework for neuroengineering. It enables direct translation of brain computational principles into engineering systems, even when we do not truly understand the purposes of the processing. Conversely, it enables us to simulate brain processes in both analog and digital computers, helping us derive and check mathematical hypothesis that furthers our understand of the brain.

We will not present in this paper the design of the analog VLSI components that were developed to implement the K0 PE. Please consult the following papers [5],[6]. We will only briefly address the design principles that were utilized and present results of our chips. Designing VLSI chips to mimic brain function is a formidable problem basically for three reasons: power consumption, size of the components and the massive interconnect. We utilized analog VLSI in subthreshold regimes to decrease the power consumption and the size. We utilized hybrid (analog amplitude/ discrete time) components to fully utilize the power of analog computation (time is a free parameter for the computational algorithms), while enabling us to multiplex signals and save real state for the interconnect.

In order to implement a K0 PE one needs to design an adder, a second order dynamic element (a lowpass filter with specified time constants), and a nonsymmetric static nonlinearity. Once this is accomplished, the KII is an arrangement of K0 and the KIII is an arrangement of KII connected by dispersive delays. The KII setup for our tests is shown in figure 4, with table I summarizing the parameter values. The results from an actual VLSI implementation are plotted in figures 5 and 6. As expected the KII behaves

as an oscillator controlled by the input. The waveform phases measured at different points of the KII follow closely the digital simulations.

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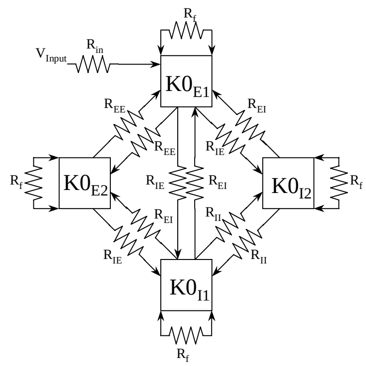

Figure 4.- KII schematic (R_F and R_{ij}; j,i=E or I, correspond to R_{sk}; k=1,..,n in figure 7, respectively).

Table 1: KII Interconnections gain

Gain	Value
$\mathbf{R_F/R_{EE}}$	2.5
$\mathbf{R_F/R_{II}}$	2.5
$\mathbf{R_F/R_{IE}}$	2
$\mathbf{R_F/R_{EI}}$	5

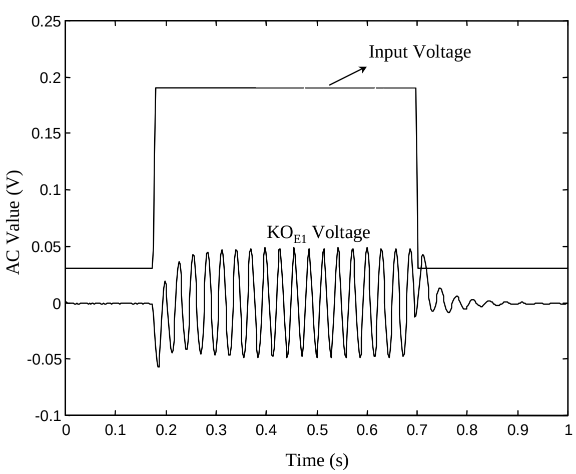

Figure 5.- Measured KII oscillatory behavior with the input.

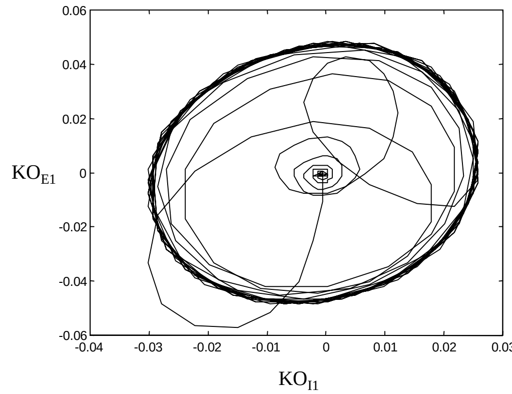

Figure 6.-Measured KII phase plot showing a complete cycle correspondent to figure 11. All K0 cells in figure 10 oscillate at the same frequency but out of phase.

As can be seen in figure 6, the state of a KII PE has two stable regimes: a fixed point at the origin, and a limit cycle. The transition between these two points is controlled by the input. This attractor has been called a Shilkonov attractor. When a 20 bit input stream is presented to a KII network, and the excitatory connections are modified with Hebbian learning the OB PEs display oscillations of different amplitudes, coding “1” as high amplitude, and “0” as low amplitude oscillations as shown in Figure 7.

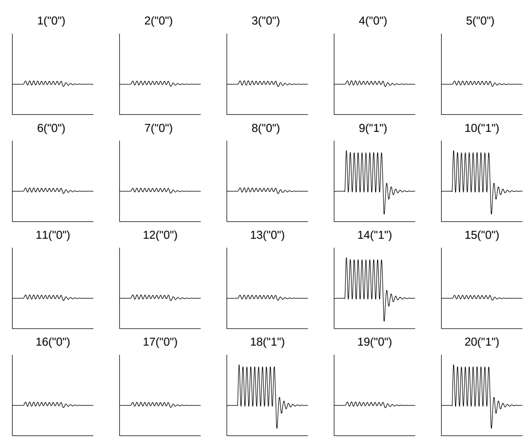

Figure 7. Oscillatory patterns over a 20 PE OB layer. Channels that have a high amplitude codify “1” in the input pattern.

We still do not have chip simulations for the KIII network. Our simulation of the dynamics using digital signal processing techniques [4], show that in fact the KIII model has nonconvergent dynamics, possibly chaotic [4]. Instead of sinusoids of different amplitudes, signals have a much more complex time structure, but are still modulated in the same way (i.e. KII PEs that codify “1” have higher amplitude). Figure 8 shows phase plots of a KIII network simulation taken at different points in the hierarchy. We see

trajectories that are compatible with a chaotic attractor, as discussed by Freeman [7].

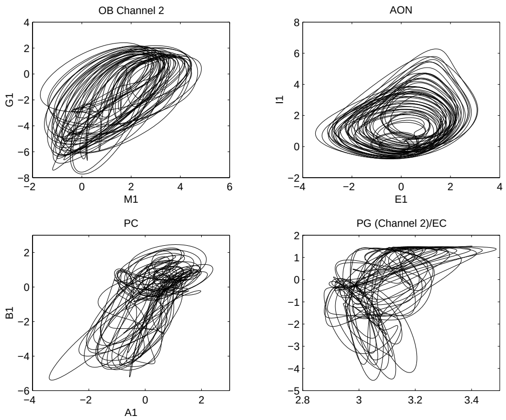

Figure 8. Phase plots at different levels of the KIII hierarchical model of the olfactory cortex without an input, simulated in a digital computer. The plots are compatible with a chaotic attractor.

4. CONCLUSION

This paper starts by posing the important question of how to translate signals into symbols preserving maximally the information in the signal time structure. From biological studies, it seems that the brain of mammals solves the problem by coupling the sensory inputs to locally stable but globally unstable dynamical lattices of rather simple nonlinear dynamical processing elements.The language of dynamics helps us simulate and implement in analog VLSI circuits with similar dynamics. Hence, this opens up the possibility of creating brain dynamics in chips that can be used to create animats which may display the same sensitivity, selectivity, adaptiveness, speed, and tolerance to noise that characterizes human sensation.

5. ACKNOWLEDGMENTS

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